

Stable Autoencoding: A Flexible Framework for Regularized Low-Rank Matrix Estimation

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Abstract

Low-rank matrix estimation plays a key role in many scientific and engineering tasks, including collaborative filtering and image denoising. Low-rank procedures are often motivated by the statistical model where we observe a noisy matrix drawn from some distribution with expectation assumed to have a low-rank representation; the statistical goal is then to recover the signal from the noisy data. Given this setup, we develop a framework for low-rank matrix estimation that allows us to transform noise models into regularization schemes via a simple parametric bootstrap. Effectively, our procedure seeks an autoencoding basis for the observed matrix that is robust with respect to the specified noise model. In the simplest case, with an isotropic noise model, our procedure is equivalent to a classical singular value shrinkage estimator. For non-isotropic noise models, however, our method does not reduce to singular value shrinkage, and instead yields new estimators that perform well in experiments. Moreover, by iterating our stable autoencoding scheme, we can automatically generate low-rank estimates without specifying the target rank as a tuning parameter.

Keywords: Artificial data corruption, correspondence analysis, parametric bootstrap